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RESEARCH ARTICLE

OPTICALS: A Novel Framework for Optimizing Predictive Trading Indicators in Cryptocurrency Using Advanced Learning Simulations

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ABSTRACT Cryptocurrencies have reshaped finance with secure, decentralized trading, attracting investor interest due to high volatility and potential returns. Accurate price forecasting is essential for optimizing returns and managing risks in digital markets. This study introduces OPTICALS, a novel framework for daily cryptocurrency price forecasting, focusing on transparency, robust performance assessment, and interpretability in machine and deep learning models. Unlike existing methods, OPTICALS provides detailed insights into model predictions by optimizing hyperparameters and identifying each model's strengths and limitations. The framework evaluates five models–XGBoost, LightGBM, LSTM, Bi-LSTM, and GRU–on three major cryptocurrencies: Ethereum, Binance, and Solana, known for high trading volumes and distinct characteristics. OPTICALS incorporates a ''Look-back window'' hyperparameter, using recent historical prices to predict next-day trends through Moving Averages analysis. This parameter refines lagged feature engineering to enhance trend capture and predictive accuracy. Models underwent rigorous evaluation, including multiple simulations and hyperparameter tuning. Gradient Boosting models were tuned via GridSearchCV and regularization to improve performance through diverse ensembles. RNN models were optimized by adjusting neurons, stacks, epochs, batch sizes, and optimizers. Predictions were validated against one-week-ahead prices to ensure robust accuracy. Findings show that GRU and XGBoost excel at predicting real-time trends, with GRU supporting day trading and XGBoost benefiting swing trading. This study advances cryptocurrency analytics, providing practical forecasting tools for traders, investors, and institutions to navigate volatility and manage risks effectively.

INDEX TERMS Cryptocurrency return, deep learning, machine learning, lagged feature engineering, gradient boosting, recurrent neural networks.

I. INTRODUCTION

Cryptocurrencies are decentralized digital assets that have revolutionized digital marketing and trading flows without fees, built on advanced and secured blockchain (BC) technology [1]. BC enables secure peer-to-peer transactions by allowing users to exchange value directly without intermediaries as first conceptualized by Nakamoto, who introduced the pioneering digital currency, Bitcoin [2]. In addition to reshaping the financial ecosystem, cryptocurrencies have provided secure, decentralized alternatives to traditional fiat currencies. Since Bitcoin's inception, numerous other cryptocurrencies with distinct features and functionalities have emerged. Notably, stablecoins like Ethereum (ETH), Binance (BNB) Coin, and Solana (SOL) have gained significant attention for their capacity to maintain

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value stability by being linked to external assets, including fiat currencies or commodities. This stability makes these digital currencies ideal for applications like international trade, remittances, and hedging against market volatility. Despite their stability, the broader cryptocurrency market remains volatile, prone to sudden price fluctuations. Therefore, designing efficient algorithms to capture market trends and dynamics accurately is essential for ensuring reliable and adaptive forecasting for the proposed coins.

Cryptocurrency presents significant investment opportunities globally. In addition to their role in reshaping the financial ecosystem, users typically acquire USD Tether (USDT) via web or mobile applications on Android and iOS platforms, enabling them to purchase cryptocurrencies at prevailing market values. Given the market's high volatility, investors closely monitor real-time buying and selling trends through widely used platforms such as CoinMarketCap and Binance. Accurate cryptocurrency price prediction is crucial for financial analysis, aiding investors in making informed decisions and anticipating market trends. Machine learning (ML) and deep learning (DL) models are pivotal in predicting cryptocurrency prices, assisting investors in making informed decisions while minimizing risks. These predictions help investors make timely, well-founded decisions while mitigating misinformation spread by profiteers and fraudsters. However, despite advancements in these techniques, predicting cryptocurrency prices remains challenging due to the market's highly volatile nature [3]. Traditional forecasting models, such as AutoRegressive Integrated Moving Average (ARIMA) and Seasonal-ARIMA (SARIMA), struggle to capture the complex, non-linear patterns inherent in these predictions [4]. Recently, machine learning ensemble techniques like gradient boosting and advanced Recurrent Neural Network (RNN) architectures, including Long Short-Term Memory (LSTM) networks have exhibited superior performance in forecasting time series data [5], offering robust solutions for tackling these complexities. Nevertheless, it remains essential for researchers and financial professionals, including analysts, investors, and traders, to continue refining these models and techniques to improve further accuracy and reliability in the highly dynamic cryptocurrency market [6].

This research examines three of the top ten cryptocurrencies by trading volume: Ethereum (ETH), Binance Coin (BNB), and Solana (SOL), each playing a pivotal role in the evolution of blockchain and digital assets. ETH, the native currency of the Ethereum blockchain, is recognized as a pioneering platform for programmable blockchain technology. As the second-largest digital coin, ETH serves various purposes, including payments, decentralized finance applications, and rewards for miners within the Ethereum network. With the rollout of Ethereum 2.0, ETH is transitioning from a Proof of Work (PoW) consensus model to a Proof of Stake (PoS) mechanism to enhance scalability and energy efficiency, while maintaining decentralization through validator participation and staking. SOL coin, a newer cryptocurrency, combines Proof of History (PoH) with PoS to achieve high throughput and low latency by optimizing performance while balancing decentralization. BNB, the native token of the BNB exchange, has become widely popular in the digital market. It supports the BNB ecosystem by offering users lower transaction fees, access to token sales, and additional features such as staking and lending [7], [8], [9], [10]. The selection of these digital coins and their distinct price dynamics is well-founded for this research. Their unique technological innovations, substantial market capitalization, and significant influence on the cryptocurrency ecosystem make them ideal candidates for analyzing price trends and developing robust forecasting models. By implementing ML and DL algorithms that utilize accurate historical market data for these digital coins, this research seeks to provide accurate and timely predictions. This study contributes to market analytics, offering valuable insights to help investors and market participants improve their risk management and investment strategies.

A. THE RESEARCH CONTRIBUTIONS

The key findings of this research are as follows:

1) This study proposes a novel framework, OPTICALS (**O**ptimizing **P**redictive **T**rading **I**ndicators for **C**ryptocurrency with **A**dvanced **L**earning **S**imulations), which leverages machine and deep learning techniques to determine the optimal models for forecasting prices of high-volatility cryptocurrencies. OPTICALS bridges existing gaps by addressing the need for actionable forecasting, emphasizing transparent, date-specific price predictions for traders and financial institutions. It focuses on extensive model optimization in training both Gradient Boosting and Recurrent Neural Network (RNN) architectures and incorporates, for the first time, the 'Look-back Window' as a hyperparameter in model training. This parameter customizes historical data selection for sequential next-day predictions using Moving Averages analysis, refining lagged feature engineering and enhancing prediction accuracy. Unlike prior approaches that prioritize model training accuracy without addressing date-wise forecasting, OPTICALS provides insights into model performance under optimized settings and clearly delineates each model's strengths and limitations. Through systematic evaluation, it aims to support accurate, informed decision-making in cryptocurrency trading.
2) This study systematically evaluates advanced Machine and Deep Learning algorithms to generate precise 7-day price forecasts for high-volume cryptocurrencies, focusing on Ethereum, Binance, and Solana, which rank among the top 10 by trading volume. By examining hyperparameter optimization alongside the Look-back Window parameter setting, this research delivers accurate date-specific

forecasting, addressing the critical gap in the literature, where model accuracy is emphasized over actionable price forecasting. Within the OPTICALS framework, GRU demonstrates robust performance in capturing real-time market dynamics, supporting short-term trading strategies, while XGBoost effectively models medium-term price trends, facilitating swing trading and long-term investment decisions. These insights enhance decision-making for traders and financial institutions, improving the reliability of trading strategies in the volatile cryptocurrency market.

3) This study offers the first comprehensive assessment of gradient-boosting and RNN techniques for forecasting highly nonlinear cryptocurrency prices, with a focus on their ability to predict price stability (retention) for Solana and price fluctuations for Ethereum and Binance Coin. Both gradient-boosting models and RNN architectures show strong predictive performance, achieving optimal calibration within the OPTICALS framework without any signs of overfitting or underfitting.

B. IMPLEMENTATION PROCEDURE

Numerous crucial aspects are involved in implementing ML and DL algorithms for date-wise digital currency price forecasting to ensure accurate and trustworthy predictions by the proposed novel framework. This research concentrates on OPTICALS framework aimed at enhancing comprehension and emphasizing the transparency of the process for each ML model. Hence, the overview of the methodological processes is outlined as follows:

a. **Data Acquisition:** We will obtain accurate historical data on highly volatile coins from reliable sources. Essential features like total volume, open-close price, and high volume will also be considered.

b. **Data Preprocessing:** The dataset will undergo preprocessing to identify underlying patterns, ensure data cleaning, address overfitting, detect outliers, and standardize features before training.

c. **Exploratory Data Analysis:** Descriptive statistics will be computed to analyze each feature in detail and discover relationships.

d. **Feature Engineering & Selection:** Some feature engineering methods will extract significant characteristics, such as moving averages, volatility metrics, and trading indicators that reflect market dynamics. Based on the problem domain, we will select the relevant features for training purposes.

e. **Machine & Deep Learning Modeling:** We will train non-linear supervised learning models multiple times to ensure robust results. We will compare the performance of ML models utilizing boosting techniques like LightGBM and XGBoost with variants of advanced RNN techniques such as LSTM, BiLSTM, and GRU to identify the best predictors for financial market analysts.

f. **Validation & Optimization Process:** The built algorithms will be assessed using various evaluation metrics, including MAE, RMSE, MSE, MAPE, and R-Squared. Appropriate cross-validation techniques such as GridSearchCV or randomSearchCV will be employed on the ML models, whereas, for DL models, fine-tuning methods like ParameterGrid and Custom-loop will be utilized to achieve better accuracy and avoid overfitting and underfitting issues.

This research aims to identify optimal algorithms for forecasting non-linear cryptocurrency price movements, enhancing decision-making in the volatile market. The findings will advance the understanding stablecoin dynamics, improve forecasting accuracy, and provide practical tools for traders, investors, and financial institutions to navigate market volatility. By identifying practical algorithms for stablecoin forecasting, the study will help stabilize markets, boost confidence in digital assets, and enable better risk management. Ultimately, it will contribute to the broader field of cryptocurrency analytics by improving forecasting methodologies and understanding stability mechanisms.

This paper is structured as follows: Section II presents a review of related studies, while Section III outlines the materials and methods employed in the proposed solution. Section IV details the modeling, simulation, and optimization setup. The results and discussion are detailed in Section V, with the conclusion is presented in Section VI.

II. RELATED WORK

The rapidly evolving landscape of digital cryptocurrency trading has attracted the interest of investors and researchers, primarily driven by its pronounced volatility and the potential for significant returns. Accurate price forecasting is essential for effective trading in digital markets, enabling traders to optimize returns and reduce risks [11]. Therefore, developing and improving digital crypto-based price prediction using machine learning models have become vital to building successful trading strategies [12]. Despite this, research needs to improve the accuracy of the prediction of price fluctuations, mainly the top coins proposed in this paper.

The forecasted trends for the Bitcoin (BTC) digital currency have been trained on data from January 1, 2017, to October 30, 2022 [4]. The findings of this suggested study claimed that the LSTM model outperforms traditional methods such as ARIMA, Seasonal ARIMA, and FB Prophet in predicting BTC prices. However, there were no date-wise price predictions provided, and no hyperparameter optimization process was conducted, which could have enhanced the model's accuracy. Additionally, this study emphasizes the significance of coin volume in trend prediction; however, the use of five years of highly volatile seasonal data raises concerns about the potential for overfitting. Moreover, the digital coins ETH, Ripple (XRP), and BTC prices were predicted using Random Forest (RF) and Stochastic Gradient Boosting Machine (SGBM) models [13]. However, this study focused solely on model accuracy as described in [4], using MAPE as the only evaluation metric, which is insufficient for a comprehensive performance assessment. Poongodi et al., [14] and Saad et al., [15] studies analysed the exchange rates of ETH using Linear Regression (LR) and Support Vector Machines (SVM). The SVM outperforms LR by achieving higher prediction accuracy, and it is recommended that different window lengths be used for analysis. However, both studies need to present results for various window lengths and focus only on ETH, limiting its scope by excluding other cryptocurrencies. Thus, the findings may generalize poorly to the broader cryptocurrency market. Rather [16] studies have combined SVM, Deep Neural Networks, and Decision Trees and called them Combined Predicted Model (CPM). The CPM model demonstrated better performance compared to individual models. This study [16] emphasized the use of the Auto-Correlation Function (ACF) to assess the similarity of time series and its lagged form, using R-squared and RMSE as validation metrics. Similarly, this study has the same limitation as aforementioned by not focusing on providing predicted prices.

Recent studies have shown that the ensemble learning models are effective for time-series forecasting due to their resistance against data overfitting, although their studies still have limitations of the price prediction accuracy issue as aforementioned in [11]. Authors Swati and Mohan [17] applied XGBoost, AdaBoost, and CatBoost to predict Bitcoin (BTC) and Ripple prices. The suggested study by S. Swati and A. Mohan demonstrated the potential of a simple boosting strategy, with AdaBoost outperforming XGBoost and CatBoost. However, comprehensive evaluation and proper optimization steps are required to improve the model performance further. Similarly study with little change selection of digital coins used by Manchanda and Aggarwal [18] to explore the potential of AdaBoost for forecasting BTC, ETH, XRP, Litecoin, and Stellar. However, this study focused solely on model accuracy, using MAPE as the only performance metric that needs improvement for thorough performance assessments. Rathan et al, [19] study suggested identifying daily price fluctuations to leverage this trend for BTC analysis by employing LR and decision trees to predict five-day currency values while emphasizing the need for enhanced accuracy to better align predictions with real-time trading. Additionally, Bayesian neural networks (BNN) were compared with LR to assess prediction accuracy in real-time currency analysis by Jang and Lee [20]. As expected, the LR model struggled with non-linear data patterns, leading to suboptimal performance. However, this study is also needed to predict accurately the real-time values along with specifying the data duration used for the simulations, limiting the transparency and reliability of the results. Furthermore, Chowdhury [21] implemented advanced ML models, gradient-boosted trees, ANNs, K-nearest neighbours, and ensemble learning algorithms, using daily prices. Ensemble methods and gradient-boosted trees provided the best prediction performance, frequently surpassing other state-of-the-art models. While this study [21] presented valuable characteristics of each model, it lacks thorough cross-validation with essential hyperparameter tuning, such as regularization terms, which are crucial during training. The LightGBM, SVM, and RF have been employed as binary classification Machine Learning models to investigate and forecast various trends in cryptocurrency by Sun et al., [22]. However, this approach [22] may need to be revised, as effective trend forecasting necessitates not only the classification of trends but also an examination of non-stationary and additional analytical considerations to capture the dynamic nature of cryptocurrency markets.

Using sequential deep learning (DL) methods has achieved notable success in predicting accurate cryptocurrency prices. Pintelas et al., [23] used DL models for the prediction of cryptocurrency price and revealed the limitations in delivering reliable forecasts. Thus, this research determined that more advanced algorithms are needed to improve price prediction accuracy. To improve the prediction performances, Livieris et al., [24] have combined the ensemble strategies, including averaging, bagging and stacking techniques using hourly prediction of digital coins TBC, ETH and XRP from January 2018 to August 2019. Their results showed that combining deep learning with ensemble methods can yield robust models. Similarly, Patel et al., [25] have employed a hybrid approach that integrates LSTM and GRU layers for accurate price predicting of Litecoin and Monero coins. Further studies, such as Livieris et al., [26] and Zhang [27], introduced a hybrid CNN-LSTM model for predicting significant cryptocurrencies with promising outcomes. However, these studies overlook crucial factors, such as providing date-wise predictions, specifying prediction window sizes, and incorporating optimization processes as critical elements for building more accurate price prediction models. Seabe et al., [28] evaluated GRU, LSTM, and Bi-LSTM models for predicting the accurate exchange rates and stability of BTC, ETH, and Litecoin. However, this study is similar lacking accurate price prediction. Gunarto et al., [29], Latif et al., [30] and Wen and Ling [31] studies supported similar findings on the effectiveness of LSTM in cryptocurrency forecasting. Additionally, Hansun et al., [32] study conducted the comparative analyses of LSTM, Bi-LSTM, and GRU models across five cryptocurrencies namely, BTC, ADA, ETH, BNB, and Tether. LSTM and Bi-LSTM consistently outperformed other models in forecasting accuracy, but the studies did not consider different window lengths or incorporate other critical cryptocurrencies, limiting their scope. Finally, Das et al., [33] presented a hybrid Encoder-Decoder LSTM technique, but like the other studies, this study focused mainly on model accuracy without addressing prediction windows or trend analysis.

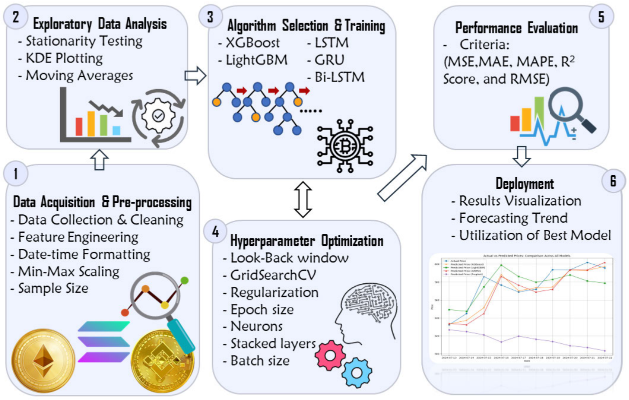

FIGURE 1. The proposed novel OPTICALS framework for robust and accurate date-wise cryptocurrency forecasting.

More consideration needs to be given to practical forecasting challenges that raise concerns about the real-world applicability of these models, which may be prone to overfitting or underfitting.

Some common limitations among the existing studies emphasise improving the accurate prediction performance with advanced models while often paying attention to essential implementation steps. These steps include ensuring decision-making transparency, conducting hyperparameter cross-validation, selecting an optimal training set, and providing date-wise interpretations of the forecasted prices. Although many studies focused on enhancing model accuracy, they frequently overlooked the complexities of cryptocurrency analysis, particularly its non-stationary nature as factors critical for investors seeking reliable and detailed price predictions. Moreover, more than relying solely on evaluation metrics is needed; combining date-wise price predictions across multiple coins with these metrics is crucial for supporting informed decision-making strategies.

III. MATERIALS AND METHODS

This study aims to forecast the daily prices of three prominent cryptocurrencies–Ethereum, Binance Coin (BNB), and Solana–selected for their market significance and price volatility. The forecasting is performed using five advanced machine and deep learning models: XGBoost, LightGBM, LSTM, GRU, and Bi-LSTM.

The methodology follows a structured framework termed OPTICALS, designed to ensure transparency, robust performance assessment, and interpretability of each model. As illustrated in Figure 1, the framework integrates multiple stages, including data preprocessing, feature engineering, model training, and performance evaluation. Each model undergoes rigorous cross-validation and multiple simulation runs to optimize predictive accuracy across key evaluation metrics.

The subsequent sections provide a detailed breakdown of the experimental procedures, focusing on the unique contributions of the OPTICALS framework.

A. DATA ACQUISITION AND PRE-PROCESSING

The dataset comprises daily prices for Ethereum, Binance, and Solana, obtained from Yahoo Finance and covering daily prices for the year 2024, with corresponding dates from January 1, 2024, to August 20, 2024. This timeframe is selected to capture current market trends and maximize relevance in forecasting analysis. Each coin's data is treated independently as a univariate time series to effectively model and predict price fluctuations.

In the pre-processing stage, essential steps are taken to prepare the data for ML and DL models. First, data cleaning and outlier detection are conducted using the InterQuartile Range (IQR) method, reducing noise and improving data quality. The dataset is then restructured by indexing coin prices with date-time formatting, preparing it for sequential time-series modeling.

Feature scaling is applied using the *Min-Max Scaler* function, which normalizes values to a standardized range of [0, 1]. This step is essential for effective model training, as it ensures all features are on a comparable scale, thereby optimizing model performance for sequential analysis. Following normalization, the data splitting operation is performed, where the final week of each dataset is set aside as a test set to assess model performance on unseen data, while the remaining portion of the data is used to train the models.

An important aspect of this analysis within the proposed OPTICALS framework is the application of a *look-back* window, which leverages recent historical prices to predict the next day's value. This *look-back* window, treated as a hyperparameter, is iteratively tested and optimized for each coin and model type to enhance predictive accuracy. Specifically, for the LSTM models, a 5-day look-back period is applied to predict ETH, 7 days for BNB, and 13 days for SOL. In contrast, for the XGBoost and LightGBM models, a 7-day look-back period is used for both ETH and BNB, while an 11-day period is more effective for SOL. This tailored hyperparameter tuning, achieved through multiple simulations, demonstrates that setting model-specific look-back values significantly improves prediction accuracy, enabling the models to capture recent trends more effectively.

The pre-processing steps, including outlier removal, feature scaling, data splitting, and iterative hyperparameter tuning, establish a robust foundation for the modeling phase. These operations ensure that the data is optimally prepared for accurate forecasting, leading to reliable and interpretable results in predicting daily price movements for these coins.

B. EXPLORATORY DATA ANALYSIS

Descriptive analytics of each coin dataset have been conducted to assess stationarity and calculate moving averages with window sizes of 5 to 10, guided by a p-value threshold of 0.5, depicted in Figures (5-7) for ETH, BNB, and SOL respectively. These moving averages are crucial for determining the optimal look-back window size hyperparameter, enabling models to incorporate recent historical prices for predicting the next day's value.

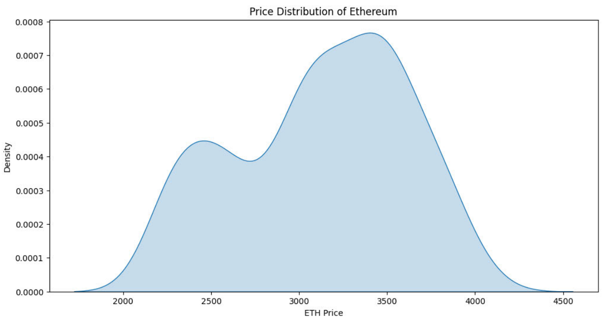

FIGURE 2. KDE plot of training data showing Ethereum price distribution.

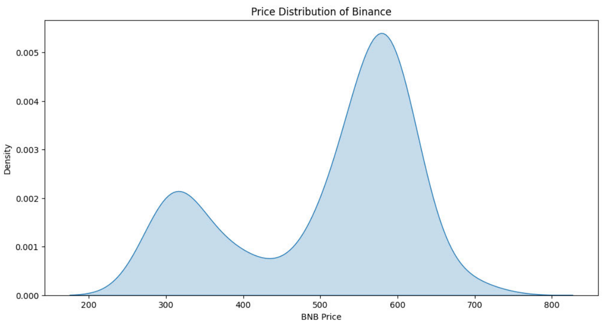

FIGURE 3. KDE plot of training data showing Binance price distribution.

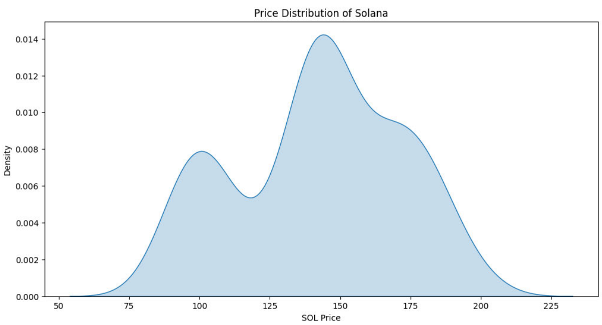

FIGURE 4. KDE plot of training data showing Solana price distribution.

These exploratory analyses are essential for selecting appropriate machine and deep learning models, determining suitable cross-validation techniques, and defining specific hyperparameters for model training. The distributional properties of each coin's data are visualized using Kernel Density Estimation (KDE) plots, as shown in Figures (2-4). These plots provide insights into underlying patterns and trends, which help in understanding price behavior over time and adjusting lagged features for model training.

C. ADVANCED PREDICTIVE MODELING TECHNIQUES

This section presents the machine learning and deep learning models utilized for cryptocurrency price forecasting within the OPTICALS framework. The predictive models were selected based on their ability to handle complex, non-linear, and volatile time-series data.

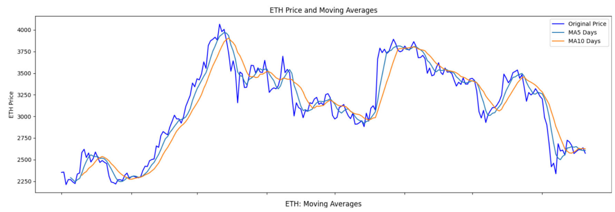

FIGURE 5. Ethereum moving average analysis of 5-10 days using interquartile range.

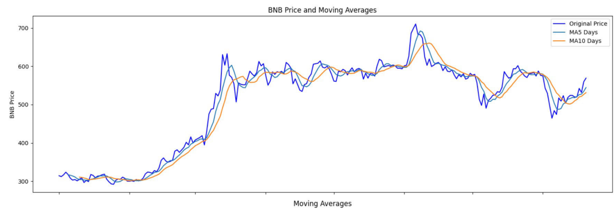

FIGURE 6. Binance moving average analysis of 5-10 days using interquartile range.

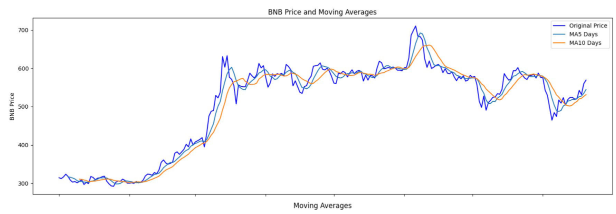

FIGURE 7. Solana moving averages analysis of 5-10 days using interquartile range.

1) GRADIENT BOOSTING TECHNIQUES

Gradient boosting techniques is a powerful ensemble learning approach that iteratively refines weak predictive models to improve forecasting accuracy. This approach iteratively trains each model to correct the errors made by its predecessor, allowing the final ensemble to achieve superior predictive accuracy. This study employs XGBoost and LightGBM, two widely recognized gradient boosting algorithms, due to their computational efficiency and adaptability to volatile financial data.

XGBoost enhances predictive accuracy by incorporating regularization techniques and optimizing computational efficiency. To fine-tune performance, nine hyperparameters were optimized using GridSearchCV, ensuring robust model training for each cryptocurrency. Additionally, the Look-back Window parameter was integrated into the input structure to capture temporal dependencies effectively.

LightGBM optimizes boosting efficiency through Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). GOSS works by excluding a large portion of data points with small gradients, focusing only on the remaining instances to compute the information gain, thereby enabling accurate estimations with a reduced dataset size. EFB groups mutually exclusive features, reducing the feature set and enabling faster computations without sacrificing accuracy. Its optimization function, based on Newton's method, constructs an ensemble of multiple regression trees to create the predictive function. These techniques reduce computational overhead while maintaining high accuracy, making LightGBM well-suited for large-scale forecasting tasks.

Both models' objective functions in cryptocurrency forecasting are presented in Equation 1, with further details on hyperparameter optimization provided in Table 1 and the Hyperparameter Optimization subsection.

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{Y}_i) + \sum_{k=1}^{K} \pi(h_k) \tag{1}$$

The objective function $L(\theta)$ comprises two primary components: the loss function $\sum_{i=1}^{n} l(y_i, \hat{Y}_i)$, which quantifies the prediction error between the actual values y_i and the predicted values $\hat{Y}i$, and the regularization term $\sum_{k=1}^{K} \pi(h_k)$, which regulates the model's complexity. Here, K represents the number of trees in the ensemble, while $\pi(h_k)$ for each tree k is defined by the equation 2.

$$\gamma T + 1/2\lambda \sum_{j=1}^{T} w_j^2 \tag{2}$$

Here, T represents the total No. of leaves, w_j represents the weights associated with each leaf, and γ and λ are the regularization terms that balance the trade-off between model accuracy and complexity to prevent overfitting. The price prediction for day t is calculated using equation 3.

$$Y^t = \sum_{k=1}^{K} h_k(X_t - 1, X_{t-L+1}, \ldots, X_{t-1}) + \epsilon_t \tag{3}$$

where h_k represents the kth decision tree in the ensemble, which processes input feature(previous price) derived from the Look-back Window of L days. The term $X_t - 1, X_{t-L+1}, \ldots, X_{t-1}$ indicates the historical input features used for prediction, capturing the temporal dynamics of the cryptocurrency prices. The variable K denotes the total number of trees in the ensemble model, each contributing to the final prediction. Finally, ϵ_t represents the error term, accounting for any deviations between the predicted value and the actual observed price at time t.

2) RECURRENT NEURAL NETWORK ARCHITECTURES

RNN-based architectures, characterized by their unique recurrent connection structures, have demonstrated significant efficiency in identifying complex interrelationships within time-series data. For cryptocurrency price forecasting, advanced RNN architectures, including LSTM, BiLSTM, and GRU, have proven effective in capturing the temporal dependencies in high-volatility cryptocurrencies. LSTM and its variants incorporate "gates" to retain information across longer input sequences, making them especially effective for time-series forecasting.

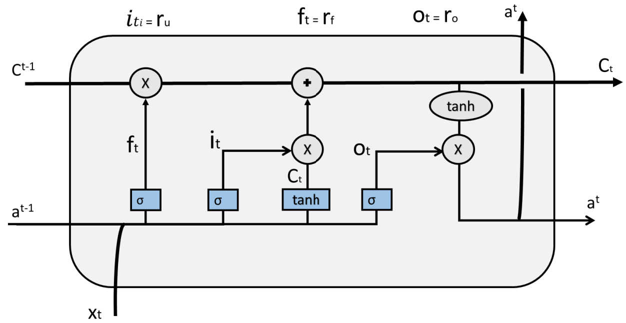

FIGURE 8. Overview of the LSTM model workflow.

The Long Short-Term Memory (LSTM) model is designed to capture temporal dependencies in sequential data, such as daily cryptocurrency prices, by regulating information flow through three gating mechanisms: the input gate i_t, the forget gate f_t, and the output gate o_t, as illustrated in Figure 8. At each time step t, the LSTM cell processes the present input x_t, the previous hidden state a_{t-1}, and the previous cell state C_{t-1}.

The forget gate f_t, determines whether past information in C_{t-1} should be retained or discarded. The input gate i_t regulates how much new input x_t contributes to the cell state. A candidate cell state $\tilde{C}_t$ is generated using *tanh* activation function, incorporating information from both i_t and a_{t-1}. The cell state is then updated by integrating retained past information with the new candidate state.

The output gate o_t, also governed by a sigmoid activation function, decides which parts of C_t influence the new hidden state a^t. The hidden state undergoes a *tanh* function to regulate the final output, which carries both short-term and long-term trends in price movements. By dynamically adjusting information retention and update mechanisms, LSTM effectively models complex, non-linear dependencies in highly volatile cryptocurrency markets.

A Bidirectional LSTM (BiLSTM) enhances the LSTM architecture by processing input sequences in both forward and backward directions via two LSTM layers. Unlike a standard LSTM, which processes sequences in a single direction, BiLSTM enhances feature extraction by capturing dependencies from both past and future time steps. This dual processing approach enables the neural network to take into account both historical trends and market expectations, which is particularly advantageous for cryptocurrency forecasting. The forward LSTM layer processes data in chronological order, while the backward LSTM layer moves in reverse. The outputs from both directions are then integrated at each time step to generate the final bidirectional output sequence. This bidirectional mechanism enables the model to capture more intricate dependencies within time-series data, leading to improved forecasting accuracy. Similar to standard LSTMs, both layers employ gating mechanisms to regulate the flow of information, ensuring efficient learning of complex temporal patterns, as depicted in Figure 9.

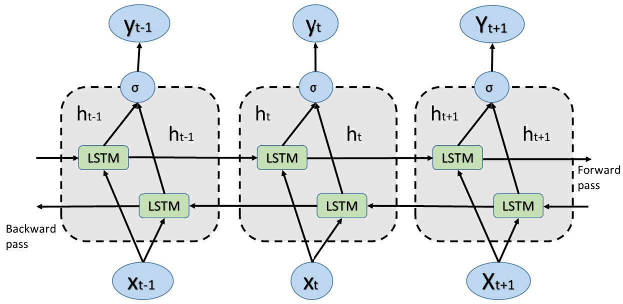

FIGURE 9. Flowchart of the bidirectional LSTM architecture.

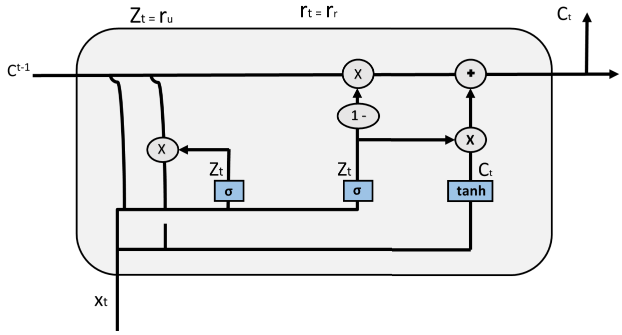

FIGURE 10. Workflow of the gated recurrent unit architecture.

The Gated Recurrent Unit (GRU) is a computationally efficient variant of LSTM that maintains comparable predictive performance while reducing model complexity. Unlike LSTM, which employs separate input and forget gates, GRU consolidates these functions into a single update gate, decreasing the number of trainable parameters and enhancing memory efficiency. GRU operates with two key gates: the reset gate, which determines how new input interacts with the previous hidden state, and the update gate, which controls the extent to which past information is carried forward. When the update gate is set to 1, past information is fully retained, whereas a value of 0 leads to complete replacement with new data. Unlike LSTM's forget gate, which selectively retains past information, GRU either fully preserves or discards previous memory states based on the update gate's value. This structure allows GRU to achieve faster training times while still effectively capturing long-term dependencies in time-series data, making it a competitive alternative for cryptocurrency price forecasting, as shown in Figure 10.

Using these architectures, cryptocurrency price forecasting models can effectively learn temporal patterns and adapt to market fluctuations, improving predictive performance in highly volatile trading environments.

In this study, these models were trained on pre-processed datasets of each coin, utilizing lagged features to capture temporal dependencies. The Adam optimizer was applied to efficiently adjust neural network weights, enhancing the optimization process. A look-back window was defined to incorporate historical data into model training, and hyperparameter tuning was performed through multiple optimization cycles to fine-tune each model for ETH, BNB, and SOL price predictions.

For initial training, models were set with 100 neurons, and further tuning was conducted to determine the optimal neuron counts. For ETH, the ideal neuron count was found to be 50 for LSTM, BiLSTM, and GRU. For BNB, the optimal configuration included 50 neurons for LSTM and 100 for BiLSTM and GRU, while for SOL, 100 neurons were optimal for LSTM and GRU, with 50 for BiLSTM. Each cryptocurrency was trained using customized settings, with 100 epochs for ETH and 50 epochs for BNB and SOL, and a consistent batch size of 32.

Multiple simulations were then performed to evaluate the forecasting accuracy of each model across the cryptocurrencies.

D. HYPERPARAMETER OPTIMIZATION

Optimizing hyperparameters is essential for enhancing the precision of both machine and deep learning models, especially in complex applications like cryptocurrency forecasting. Effective hyperparameter tuning allows models to adapt to the non-linear and volatile patterns characteristic of financial data, improving predictive stability and overall performance. Initially, tuning is performed to identify the optimal look-back window size for each model, with ideal values determined through iterative testing. These optimized look-back windows help prepare the training data to improve prediction accuracy, as discussed in the Data Acquisition and Pre-processing section. To ensure robust predictions, an extensive cross-validation process is implemented for each model during training.

For gradient boosting techniques, the *GridSearchCV* technique is employed for an extensive search across the hyperparameter space, enabling precise fine-tuning for optimal model performance. The process iterates over key hyperparameters, with negative MSE used as the evaluation metric. Multiple simulations are conducted to identify parameter combinations that maximize prediction accuracy. Key hyperparameters, outlined in Table 1, are optimized and iterated over their corresponding values, which were carefully selected to enhance model performance for cryptocurrency price forecasting.

In gradient boosting models, key hyperparameters include the *n_estimators* parameter, which defines the number of boosting iterations, facilitating gradual convergence while balancing the risks of underfitting and overfitting. The *learning_rate* controls each tree's contribution to the overall model. Smaller values enable gradual learning, improving generalization to new data, though with longer computational time. The *subsample* parameter randomly samples a fraction of the training data for each boosting iteration, effectively preventing overfitting and promoting generalization. The *colsample_bytree* parameter specifies the fraction of features considered for each tree, fostering diversity among trees

TABLE 1. GridSearchCV hyperparameter space for gradient boosting models.

Hyperparameter	XGBoost	LightGBM
n _ estimators	200, 250	150, 200, 250
learning _ rate	0.01, 0.05	0.01, 0.05
subsample	0.7, 0.8	0.7, 0.8
colsample _ bytree	0.7, 0.8	0.7, 0.8
gamma(γ)	0, 0.1	0, 0.1
min _ child _ weight	1, 3	-
reg_alpha(Lasso)	0.1	0.1
reg_lambda(Ridge)	0.1	0.1
num _ leaves	-	31, 50
max _ depth	3, 5, 7	-1, 3, 5

and minimizing overreliance on specific features. These hyperparameters work together to develop a diverse ensemble of weak learners, enhancing predictive performance.

Regularization parameters are integral to the *GridSearchCV* process, ensuring generalization and reducing overfitting. The *reg_lambda* parameter enables L2 regularization(ridge), penalizing large weights to enhance generalization and prevent overfitting. Similarly, *reg_alpha* facilitates L1 regularization(lasso) by imposing penalties on large weights. The *gamma* parameter introduces a regularization term that controls the minimum reduction in loss required to justify a split, ensuring that splits occur only when they significantly enhance predictive performance. The *min_child_weight* parameter sets a minimum threshold for the sum of instance weights in a child node, offering a flexible means of regularization to reduce overfitting, particularly in sparse or noisy datasets. Additionally, the *max_depth* parameter limits tree depth, managing model complexity and ensuring generalizable predictions across diverse timeframes. The *num_leaves* parameter specifies the maximum number of leaf nodes in trees, providing flexible model complexity suited to the nuances of cryptocurrency price data. By adjusting this parameter, a balance is struck between accurately capturing complex price movements and avoiding overfitting. This careful selection and tuning process allows these gradient boosting models to adapt effectively to the dynamic demands of cryptocurrency data. In training LSTM models, simulations were performed to tune hyperparameters, including units, stacked, epochs, and batch_size, along with optimizer selection. The units parameter defines the number of neurons per layer, enabling exploration of various network complexities. Additionally, the stacked parameter is utilized to examine the impact of stacked layers, which can enhance the model's ability to capture complex temporal patterns in the data. The Adam optimizer is selected for its efficiency in gradient descent management. *Mean_Squared_Error* is the primary evaluation metric used to identify optimal hyperparameter settings.

For effective utilization of the trained LSTM models in cryptocurrency prediction, further tuning is conducted using a parameter grid defined as *param_Grid*, containing units and stacked parameters, allowing models to select optimal values for prediction. These models are subsequently evaluated using the performance metrics detailed in the next section.

The final hyperparameter selection for each model demonstrated optimal accuracy for seven-day price predictions. For ETH predictions, the LSTM model is configured with 100 units, 100 epochs, and a batch size set to 32. Both LSTM and BiLSTM models utilize a single layer for this task, while the GRU model incorporates stacked layers. For BNB and SOL price predictions, the models are set to 50 epochs with a batch size of 32. In these cases, the LSTM and BiLSTM models are configured with stacked layers, while the GRU model employs a single layer. Finally, these trained models are applied to a test set to predict prices for the upcoming week, with further evaluation performed using metrics described in the following section.

E. PERFORMANCE EVALUATION

To rigorously assess the predictive performance of the ML and DL models and evaluate their ability to capture complex underlying patterns in the coin data, each model undergoes multiple training and testing cycles. This iterative process is conducted until optimal predictions are achieved through comprehensive hyperparameter tuning and appropriate validation protocols. The efficacy of each model is assessed using a range of performance metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Residual Score, as defined in Eq.(4-8). These metrics provide a robust framework to objectively measure model accuracy and reliability across each coin dataset.

$$\mathrm{MSE} = \frac{\sum_{d=1}^{n}(y_d - \hat{y}_d)^2}{N} \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{d=1}^{n}(y_d - \hat{y}_d)^2}{N}} \tag{5}$$

$$\mathrm{MAE} = \frac{\sum_{d=1}^{n}|y_d - \hat{y}_d|}{N} \tag{6}$$

$$\mathrm{MAPE} = \frac{100\%}{N}\sum_{d=1}^{n}\frac{|y_d - \hat{y}_d|}{|y_d|} \tag{7}$$

$$R^2 = \frac{\overline{\sigma}^2}{\sigma^2} \tag{8}$$

where N is the total number of data points, y_p is the actual cryptocurrency price, and $\hat{Y_p}$ is the forecasted price. $\overline{\sigma}^2$ represents the explained variation (sum of squared differences between forecasted and actual prices), while σ^2 denotes the total variation (sum of squared differences from the mean).

IV. MODELING, SIMULATION, AND OPTIMIZATION SETUP

This study utilized one year of historical data for Ethereum (ETH), Binance Coin (BNB), and Solana (SOL), sourced from Yahoo Finance. All experiments were conducted within the OPTICALS framework using Python in Google Colaboratory, with multiple simulations performed to optimize model performance. The experimental setup involved a PC equipped with an 11th Gen Intel Core i3 processor (2.0 GHz), 20GB of DDR4 RAM, and Windows 11 Pro, providing sufficient computational power for both ML and DL model training. Key Python libraries were used, including scikit-learn, pandas, numpy, matplotlib, seaborn, and Keras for model development. Additionally, XGBoost and LightGBM packages were integral for implementing tree-based ensemble models. Hyperparameter optimization for ML models was performed using GridSearchCV, which iteratively tuned key parameters to improve prediction accuracy. For DL models, custom modifications to the hyperparameters were made to accommodate the unique characteristics of each cryptocurrency. Performance evaluation was critical, using various metrics to assess predictive accuracy. Model predictions were validated against actual one-week-ahead price trends for each cryptocurrency, ensuring a rigorous assessment of the models' forecasting effectiveness.

V. RESULTS AND DISCUSSION

The model performance analysis under the OPTICALS framework reveals distinct patterns in predicting the price movements of Ethereum, Binance, and Solana, as presented in Tables (2-4) respectively, with varying levels of accuracy across different models. For ETH, depicted in Table 2, XGBoost achieved the lowest MSE and MAE, demonstrating its relative accuracy in tracking price trends. BiLSTM followed closely, exhibiting moderate error rates, while the LSTM and GRU models displayed higher MSE values, indicating larger discrepancies from actual values. In the case of BNB, as shown in Table 3, GRU outperformed the other models, displaying the lowest MSE and RMSE values, followed by BiLSTM and LSTM, which also performed with moderate accuracy. In contrast, the boosting techniques demonstrated higher error values for BNB compared to RNNs. For SOL, summarized in Table 4, LightGBM excelled, achieving the lowest MSE and MAE values, indicating strong predictive accuracy. GRU also performed well with competitive error values, effectively capturing Solana's trends. However, both LSTM and BiLSTM showed higher error values, indicating they were less accurate in capturing Solana's pricing patterns compared to GRU and LightGBM. Overall, GRU and XGBoost outperformed in most cases, offering commercially viable insights as reliable indicators for traders seeking predictive accuracy across diverse cryptocurrencies.

Furthermore, the computational resource utilization and training times for ML and DL models are shown in Table 5. Tree-based ML models, XGBoost and LightGBM, exhibited significantly lower training times (0.2019s and 0.1581s, respectively) with minimal memory usage. In contrast, DL models such as LSTM, BiLSTM, and GRU required much higher computational resources, with training times of 19.93s, 29.80s, and 33.44s, respectively. Additionally, GRU and BiLSTM consumed more memory (50.81MB and 52.47MB, respectively) compared to LSTM (44.74MB), reflecting the added complexity of bidirectional processing and gated mechanisms.

TABLE 2. Models' assessment for ethereum forecasting using various metrics.

Model	MSE	MAE	R^2	MAPE	RMSE
XGBoost	819.08	27.35	0.158	0.0105	28.62
LightGBM	3940.08	56.03	-3.05	0.0215	62.77
LSTM	4137.52	51.41	-3.25	0.0199	64.32
GRU	4405.49	48.24	-3.53	0.0186	66.37
BiLSTM	3067.84	42.31	-2.15	0.0163	55.39

TABLE 3. Models' assessment for binance forecasting using various metrics.

Model	MSE	MAE	R^2	MAPE	RMSE
XGBoost	277.14	13.05	0.179	0.0239	16.65
LightGBM	311.64	13.78	0.076	0.0256	17.65
LSTM	205.90	12.07	0.390	0.0221	14.35
GRU	151.36	11.43	0.551	0.0211	12.30
BiLSTM	183.80	12.99	0.455	0.0242	13.56

TABLE 4. Models' assessment for solana forecasting using various metrics.

Model	MSE	MAE	R^2	MAPE	RMSE
XGBoost	22.13	3.70	-8.41	0.0260	4.70
LightGBM	8.94	2.43	-2.80	0.0171	2.99
LSTM	11.55	2.85	-3.92	0.0200	3.40
GRU	4.08	1.58	-0.74	0.0111	2.02
BiLSTM	14.91	3.06	-5.34	0.0215	3.86

TABLE 5. Computational resources utilization and training time for models.

Model	Training Time (sec)	Memory Consumption (MB)
XGBoost	0.2019	0.00
LightGBM	0.1581	0.00
LSTM	19.93	44.74
GRU	33.44	50.81
BiLSTM	29.80	52.47

TABLE 6. Date-wise price forecasting of ethereum.

Date	Actual Price	XGBoost	LightGBM	LSTM	GRU	BiLSTM
2024-08-14	2662.91	2689.97	2726.78	2682.23	2711.19	2690.40
2024-08-15	2570.09	2608.65	2676.42	2692.60	2709.45	2689.60
2024-08-16	2593.19	2615.14	2647.51	2671.00	2651.23	2638.15
2024-08-17	2614.54	2581.45	2608.00	2654.38	2617.21	2603.64
2024-08-18	2613.35	2643.61	2577.76	2641.97	2621.0	2604.87
2024-08-19	2637.30	2627.04	2579.59	2637.51	2630.47	2612.62
2024-08-20	2573.10	2603.38	2640.96	2644.66	2647.98	2633.22

TABLE 7. Date-wise price forecasting of binance.

Date	Actual Price	XGBoost	LightGBM	LSTM	GRU	BiLSTM
2024-08-14	524.02	523.03	528.33	525.92	528.26	535.20
2024-08-15	519.87	523.21	525.97	531.92	531.42	537.19
2024-08-16	519.97	524.55	528.55	532.70	531.95	537.37
2024-08-17	542.23	522.49	528.55	534.23	530.87	537.18
2024-08-18	531.60	556.28	567.41	535.93	538.02	544.69
2024-08-19	559.81	531.16	536.05	539.66	541.97	545.95
2024-08-20	569.26	559.91	573.48	543.93	552.65	556.24

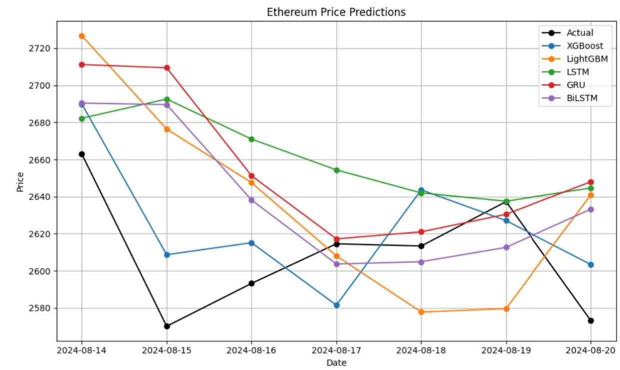

FIGURE 11. Date-wise actual vs. forecasted Ethereum trend: Gradient boosting and LSTM models.

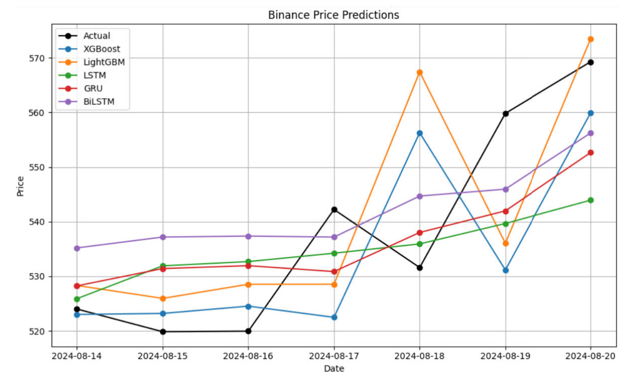

FIGURE 12. Date-wise actual vs. forecasted Binance trend: Gradient boosting and LSTM models.

TABLE 8. Date-wise price forecasting of solana.

Date	Actual Price	XGBoost	LightGBM	LSTM	GRU	BiLSTM
2024-08-14	143.92	149.00	147.70	148.51	144.48	149.15
2024-08-15	142.75	143.11	141.76	146.81	144.00	147.70
2024-08-16	139.33	144.34	144.66	145.08	143.21	146.11
2024-08-17	141.79	135.80	139.91	142.98	141.20	143.75
2024-08-18	142.58	142.74	143.05	141.86	140.79	143.0
2024-08-19	144.34	145.50	143.56	141.58	141.51	142.88
2024-08-20	143.16	151.32	146.98	142.29	143.01	143.77

A. DATE-WISE PREDICTION ANALYSIS

The date-wise prediction graphs illustrate the trend-following abilities of each model, showing actual prices alongside forecasts over a seven-day period for each coin. In Ethereum forecasting, GRU and XGBoost closely track actual prices, as depicted in Table 6 and Figure 11, accurately capturing upward and downward trends. LightGBM diverges slightly, and BiLSTM and LSTM show greater deviations, particularly

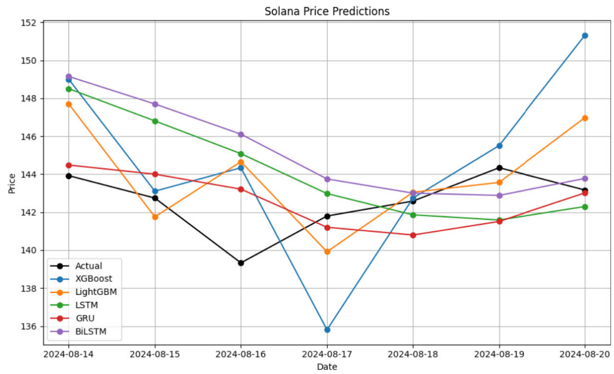

FIGURE 13. Date-wise actual vs. forecasted Solana trend: Gradient boosting and LSTM models.

during price peaks. GRU and XGBoost also stand out in Binance's line graphs Figure 12, capturing essential price movements with high alignment, especially during price rises. LSTM performs similarly, while LightGBM and BiLSTM struggle to match upward and downward price shifts as accurately, leading to moderate deviations. The date-wise actual and predicted prices for Binance are shown in Table 7. For Solana predictions, presented in Figure 13, GRU and XGBoost again emerge as strong trend followers, closely reflecting Solana's short-term volatility, as seen in Table 8. LSTM and BiLSTM offer more moderate trend tracking, while LightGBM demonstrates the least alignment with actual price movements, often lagging or overshooting price shifts.

Further validation of the models is provided by assessing their ability to predict price retention in Solana, where the price on the first and last day of the week in the test set remains the same, with minimal variability throughout the week. Both boosting techniques and GRU demonstrated this capability, indicating that the models were effectively trained within the OPTICALS framework, without overfitting or underfitting. This task, which challenges models to maintain price stability (retention) over time, highlights their ability to capture and sustain consistent patterns.

These graphical analyses affirm the effectiveness of GRU and XGBoost in accurately predicting and aligning with real-time trends across all three coins, making them the most reliable models within this analysis.

B. IMPLICATIONS FOR INVESTORS

For investors and financial analysts, GRU and XGBoost models offer distinct advantages within the OPTICALS framework. GRU's strong performance in tracking real-time market fluctuations makes it ideal for day traders, while XGBoost's ability to capture medium-term price trends is well-suited for swing traders and long-term investments. By incorporating these models into forecasting platforms, traders and financial institutions can make well-informed and timely decisions, thereby enhancing the reliability of trading strategies in the volatile cryptocurrency market. Combining both models provides a balanced approach that addresses both trend-following and precise short-term prediction needs.

VI. CONCLUSION

This study explored date-wise cryptocurrency price forecasting using a novel framework termed OPTICALS, extensively evaluating the predictive accuracy of ML boosting techniques and RNN architectures–namely GRU, LSTM, BiLSTM, XGBoost, and LightGBM. Focused on three diverse coins–Ethereum, Binance, and Solana–this research sought to identify the most effective models for capturing price trends under various market conditions. A notable feature of this study is the Look-back Window hyperparameter, which customizes historical data through Moving Averages analysis to refine lagged feature engineering and enhance prediction accuracy, particularly for volatile cryptocurrency data. The models were trained on pre-processed datasets for each coin, with lagged features used to capture temporal dependencies. Each model underwent rigorous hyperparameter optimization followed by simulations and multi-metric evaluations to enhance predictive accuracy. Transparency in model performance was prioritized, with clear insights provided into the optimized settings and each model's strengths and limitations. Results indicated that GRU and XGBoost emerged as the top-performing models. GRU consistently tracked short-term price fluctuations with high accuracy, making it well-suited for high-frequency and day trading strategies. XGBoost demonstrated effectiveness in capturing medium-term trends, making it a strong candidate for swing trading and longer-term investments. While the study offers valuable insights into cryptocurrency forecasting, certain limitations must be acknowledged. External factors, such as regulatory changes, security incidents, and shifts between bull and bear market regimes, can cause sudden and unpredictable trends that challenge even well-optimized models. Another limitation is the computational time required for hyperparameter optimization through extensive simulations. Despite these challenges, this research highlights models that enable investors and financial analysts to make informed, timely decisions, thereby improving the reliability of trading strategies in a highly volatile market. Future research will enhance adaptability, enabling robust trader decision-making by integrating multi-modal data such as social media sentiment, macroeconomic indicators, and Transformer-based models. Key signals like interest rates, inflation trends, and regulatory developments can refine long-term forecasting while fusing diverse data sources with price trends will strengthen the model's resilience. Furthermore, the development of a web-based application for real-time price prediction and adaptive model selection will extend the OPTICALS framework's capabilities, establishing it as a pioneering tool for investors and traders navigating dynamic cryptocurrency markets.

DATA AVAILABILITY

The experimental data and code are hosted in a private GitHub repository. Access can be granted upon request via email(engr.hasibshamshad@gmail.com). The repository can be accessed at: https://github.com/Hasibshamshad/OPTICALS.git.

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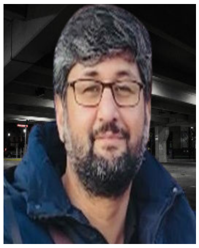

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